PARAMETER ESTIMATION OF PHOTOVOLTAIC CELL USING SWARM MVMO

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ABSTRACT

Photovoltaic solar energy has proven to be an important source in the energy transition process. However, the non-linear nature of the models used to estimate parameters makes the work difficult in an attempt to improve the efficiency of the systems. This work proposes the parameter estimation of the RTC France photovoltaic cell using the Single-diode model and the Swarm Mean-Variance Mapping Optimization algorithm. The results obtained show that the proposed algorithm is good enough for this purpose, as it achieved the same error levels as other algorithms reported in the literature and the estimated parameters achieved a good fit in the I-V and P-V curves.

Keywords: Swarm MVMO. Parameter estimation of PV systems. Single-diode model (SDM).

1. INTRODUCTION

Photovoltaic (PV) solar energy is one of the most important renewable sources in the world's energetic transition process because it is an infinite supply and combines easiness of installation, low maintenance cost, and environmental friendliness during its operation (DEMIRTAS and KOC, 2022, HUYNH et al., 2022). The non-convex, nonlinear, and multi-parameter nature of PV models hampers the work. The PV parameters estimation, which is one of the oldest research fields that remain active, is essential since the data-sheet information is insufficient and only reflects the standard test conditions (STC). Correct parameters can improve efficiency in a new project, or show the real system conditions (NGUYEN, NGUYEN, and TRAN, 2022; AGHAEI et al., 2022; BATZELIS et al., 2022). Metaheuristic methods are the most efficient for PV systems parameters estimation (ABDEL-BASSET et al., 2022). The determination of optimal unknown parameters is based on the global optimization population algorithm. The main advantages of these methods have no restriction on the objective function, continuity, and simple implementation (LUO and YU, 2022; XIONG et al., 2021).

This work proposes the parameter estimation of the Single-diode model (SDM) employing a metaheuristic method namely the Swarm Mean-Variance Mapping Optimization

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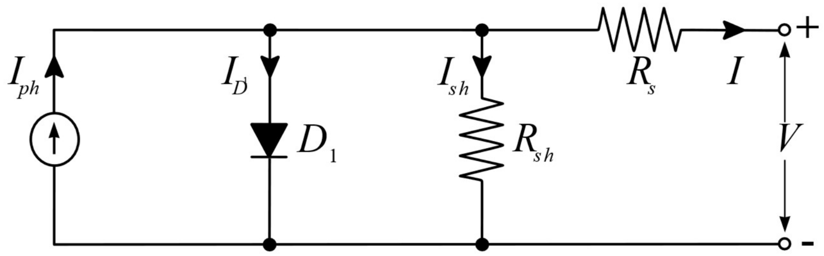
(Swarm MVMO). Measured data from the RTC France PV cell were used in this study and the results obtained were compared with others from different algorithms in the literature.

2. SINGLE-DIODE MODEL

The most common PV model used in literature is the single-diode model (SDM) due to their accuracy and simplicity (HUYNH et al., 2022). Figure 1 shows the SDM electric circuit.

Figure 1. SDM electric circuit (NGUYEN, NGUYEN, and TRAN, 2022).



According to Duman et al. (2022), applying Kirchhoff's current law to the circuit, the output current (I) is calculated by solving the implicit Eq. 1.

$$I_{ph} - I_{D1} - I_{sh} - I = 0 \qquad (1)$$

where I_{ph} is the cell photo-generated current, I_{D1} is the diode current provided by Eq. 2, and I_{sh} is the shunt resistor current,

$$I_{D1} = I_{01} \times \left\{exp\left[\frac{q \times (V + R_s \times I)}{a \times k \times T}\right] - 1\right\} \qquad (2)$$

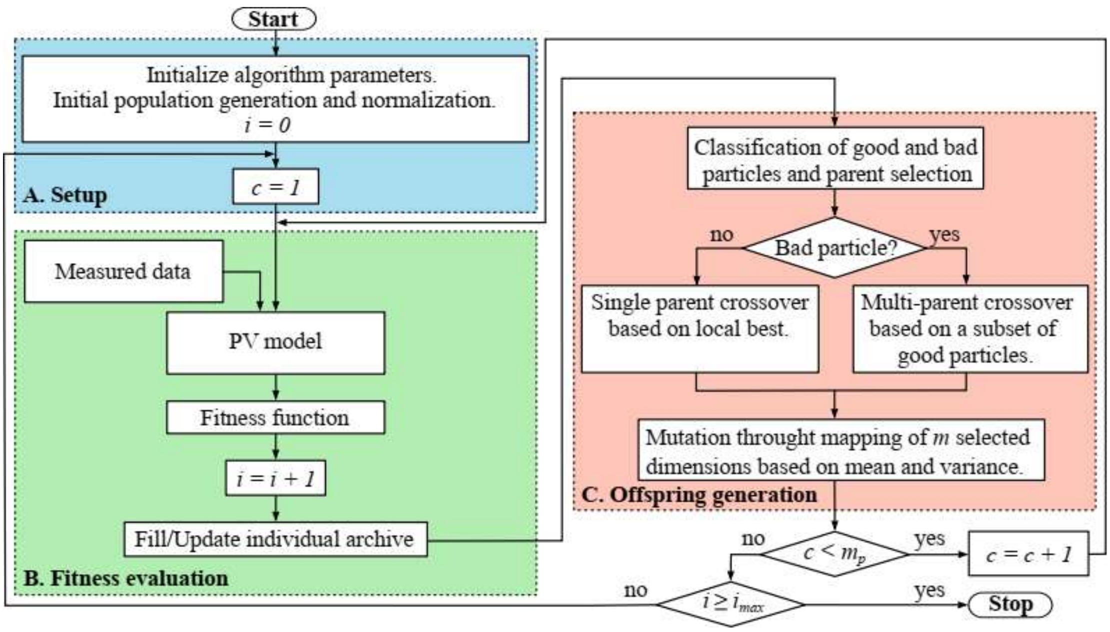
where I_{01} is the diode reverse saturation current, q is the electron charge ($1.60217646 \times 10^{-19}$ C), V is the cell output voltage, a is the diode ideality factor, k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), and T is the cell temperature. Finally, I_{sh} is given by Eq. 3. The model has 5 unknown parameters to be estimated ($p_n = 5$): I_{ph}, I_{01}, R_s, R_{sh}, and a.

$$I_{sh} = \frac{V + R_s \times I}{R_{sh}} \qquad (3)$$

3. PARAMETER ESTIMATION METHOD

The MVMO algorithm is a stochastic optimization methodology that uses concepts of selection, mutation, and crossover, resulting from evolutionary algorithms that are applied to a population and that promotes the strategic transformation of the best individuals through a mapping function. The heart of MVMO is based on its mean and variance. To extensively explore the solution space, swarm concepts were incorporated with a group of m_p particles, each having a defined memory through their archive and mapping function to collect a robust set of individual solutions. Finally, a multi-parent crossover strategy enhances search diversity, maintaining a trade-off between exploration and exploitation (ERLICH, VENAYAGAMOORTHY, and WORAWAT, 2010) (RUEDA and ERLICH, 2013). Figure 2 shows the Swarm MVMO flowchart, where i is the function evaluation counter, c is the particle counter, m_p is the number of particles, and i_{max} is the maximum number of fitness function evaluations. One of the characteristics of this method is that the parameters to be estimated must be configured at the beginning of the algorithm within maximum and minimum bounds, thus defining a search limit for each parameter.

Figure 2. Swarm MVMO flowchart – Adapted from Rueda and Erlich (2013).



According to Eq. 1 to 3 the model can be presented as a function in Eq. 4 and 5. The fitness function was calculated based on root mean square error (RMSE), described in Eq. 6 where M is the sample number.

$$f(x,y,u,r,p) = I_{ph} - I_{01}\left\{exp\left[\frac{q \times (V + R_s \times I)}{a \times k \times T}\right] - 1\right\} - \frac{V + R_s \times I}{R_{sh}} - I \quad (4)$$

$$f(x,y,u,r,p) = \begin{cases} Independent\ variable\ vector: x = [V] \\ Dependent\ variable\ vector: y = [I] \\ Input\ vector: u = [T] \\ Constants\ vector: r = [k,q] \\ Pameters\ vector: p = [I_{ph}, I_{01}, a, R_s, R_{sh}] \end{cases} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{M}\sum_{j=1}^{M} f(x,y,u,r,p)^2} \quad (6)$$

4. RESULTS AND DISCUSSION

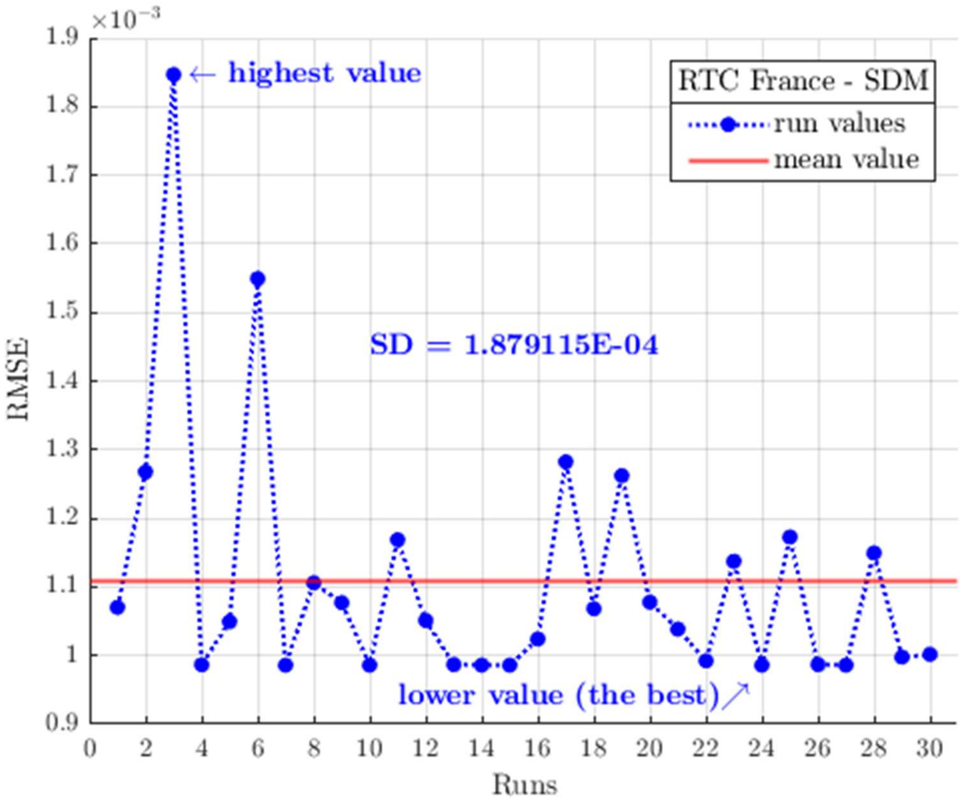
To evaluate the Swarm MVMO method for PV parameter estimation, the PV dataset of the RTC France silicon PV cell (irradiance = 1000 W/m^2 and T = 33º C) was employed as obtained in Easwarakhanthan et al., (1986), which is widely studied in the literature, as it can be seen in Demirtas and Koc (2022). The settings of the Swarm MVMO algorithm shown in Tab. 1 were based on the recommendations of Rueda and Erlich (2013) for the algorithm setup and Yaghoubi et al. (2022) for the parameters search limits. In this study, all simulations ran independently 30 times in Matlab R2022b using an 11th Gen Intel® Core™ i5-11400 @ 2.60 GHz 2.59 GHz, 24 GB RAM with Windows(R) 11, 64 bits.

Table 1. Swarm MVMO settings.

Description		Values
Number of parameters to be estimated (p_n)		5
Number of individuals per particle (X_n)		5
Maximum number of fitness functions (i_{max})		5000
Number of particles (m)		75
Simulations number (runs)		30
Search limits (lower and upper bounds)	I_{ph} (A)	0 – 1
	I_{01} (μA)	0 – 1
	a (-)	1 – 2
	R_s (Ω)	0 – 0.5
	R_{sh} (Ω)	0 – 100

After 30 runs, the lower RMSE value was 0.9860219E−03 which estimated the best PV parameters shown in Tab. 2 with other references from the literature. The highest RMSE value was 1.846593E−03, the average value was 1.108900E−03 and the standard deviation (SD) was 1.879115E−04 as can be seen in Fig. 3. The average time for one run was 97 seconds.

Figure 3. RMSE values per run.



The estimated parameters obtained by Swarm MVMO are very close to the other algorithms from the literature and indicate the efficiency of this methodology for PV parameter estimation of SDM, reaching the same level in the RMSE values. However, due to the nature of the proposed algorithm, there is a large variation in RMSE values (see Fig. 3), since the algorithm generates for each new simulation an initial random population established within the limits of each parameter. Figures 4 and 5 shows the *I-V* and *P-V* curves of the best-estimated parameters where it is possible to notice the good fit between the measured and estimated values. Table 3 shows the real measurement of current (I_{mea}), voltage (V_{mea}), and power (P_{mea}) outputs in the cell, the cell estimated output current (I_{est}) and power (P_{est}), and finally the current and power absolute errors ($|I_{ae}|$ and $|P_{ae}|$) which reached low values.

Table 2. Estimated parameters by Swarm MVMO and literature reference values from other algorithms.

Method	I_{ph} (A)	I_{01} (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE (10^{-3})
Swarm MVMO	**0.7608**	**0.3230**	**0.0364**	**53.7192**	**1.4812**	**0.986**
MSSA	0.7683	0.3262	0.0367	54.2557	1.4958	0.986
RN-ChOA	0.7608	0.3228	0.0363	53.7176	1.4811	0.976
CJAYA4	0.7608	0.3380	0.0359	52.7279	1.4857	0.986
INFO	0.7608	0.3230	0.0364	53.7185	1.4812	0.986

Note: Modified Salp Swarm Algorithm (MSSA) from Yaghoubi et al. (2022). Robust Niching Chimp Optimization Algorithm (RN-ChOA) from Bo et al. (2022). Chaotic JAYA (CJAYA4) from Premkumar (2021). Weighted mean of vectors optimization algorithm (INFO) from Demirtas and Koc (2022).

Table 3. Comparison between measured and estimated data for RTC France PV cell.

Item	V_{mea} (V)	I_{mea} (A)	I_{est} (A)	$\lvert I_{ae}\rvert$ (A)	P_{mea} (W)	P_{est} (W)	$\lvert P_{ae}\rvert$ (W)
1	-0.2057	0.7640	0.7641	0.0001	-0.1572	-0.1572	0.0000
2	-0.1291	0.7620	0.7627	0.0007	-0.0984	-0.0985	0.0001
3	-0.0588	0.7605	0.7614	0.0009	-0.0447	-0.0448	0.0001
4	0.0057	0.7605	0.7602	0.0003	0.0043	0.0043	0.0000
5	0.0646	0.7600	0.7591	0.0009	0.0491	0.0490	0.0001
6	0.1185	0.7590	0.7580	0.0010	0.0899	0.0898	0.0001
7	0.1678	0.7570	0.7571	0.0001	0.1270	0.1270	0.0000
8	0.2132	0.7570	0.7561	0.0009	0.1614	0.1612	0.0002
9	0.2545	0.7555	0.7551	0.0004	0.1923	0.1922	0.0001
10	0.2924	0.7540	0.7537	0.0003	0.2205	0.2204	0.0001
11	0.3269	0.7505	0.7514	0.0009	0.2453	0.2456	0.0003
12	0.3585	0.7465	0.7473	0.0008	0.2676	0.2679	0.0003
13	0.3873	0.7385	0.7401	0.0016	0.2860	0.2866	0.0006
14	0.4137	0.7280	0.7274	0.0006	0.3012	0.3009	0.0002
15	0.4373	0.7065	0.7070	0.0005	0.3090	0.3092	0.0002
16	0.4590	0.6755	0.6753	0.0002	0.3101	0.3100	0.0001
17	0.4784	0.6320	0.6309	0.0011	0.3023	0.3018	0.0005
18	0.4960	0.5730	0.5721	0.0009	0.2842	0.2838	0.0005
19	0.5119	0.4990	0.4995	0.0005	0.2554	0.2557	0.0003
20	0.5265	0.4130	0.4135	0.0005	0.2174	0.2177	0.0003
21	0.5398	0.3165	0.3172	0.0007	0.1708	0.1712	0.0004
22	0.5521	0.2120	0.2121	0.0001	0.1170	0.1171	0.0001
23	0.5633	0.1035	0.1027	0.0008	0.0583	0.0579	0.0004
24	0.5736	-0.0100	-0.0092	0.0008	-0.0057	-0.0053	0.0004
25	0.5833	-0.1230	-0.1244	0.0014	-0.0717	-0.0726	0.0008
26	0.5900	-0.2100	-0.2092	0.0008	-0.1239	-0.1234	0.0005
		Sum of absolute error		0.0178			0.0067
			RMSE	0.0008			0.0003

Figure 4. The measured and estimated data: I-V curve.

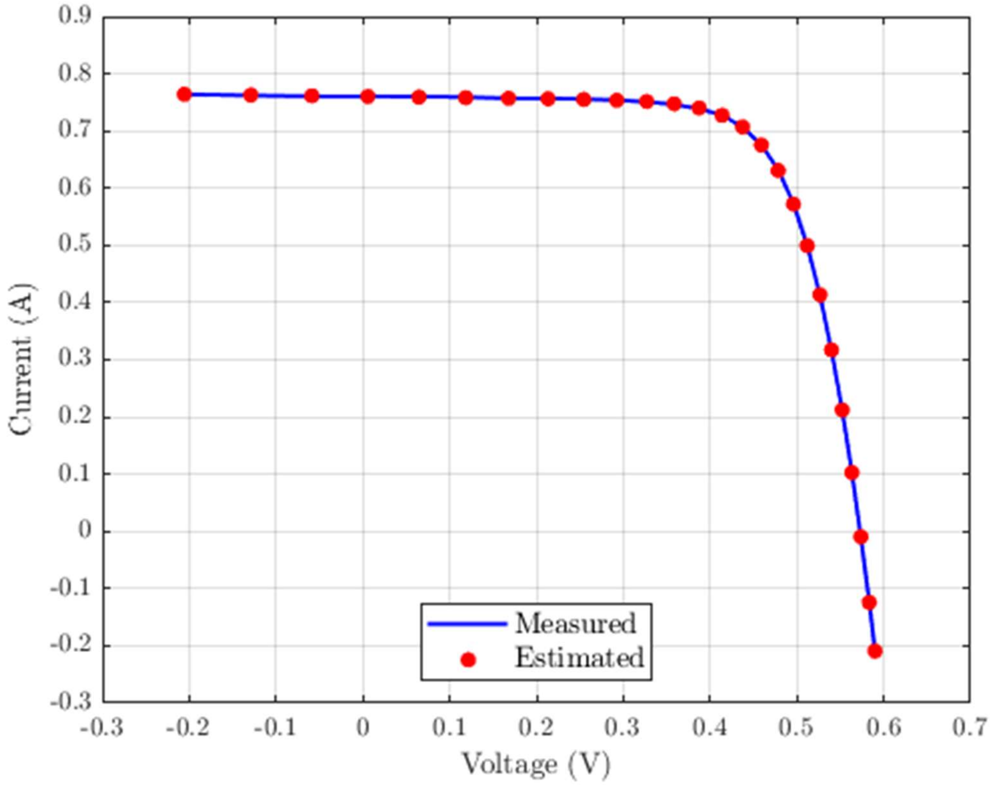
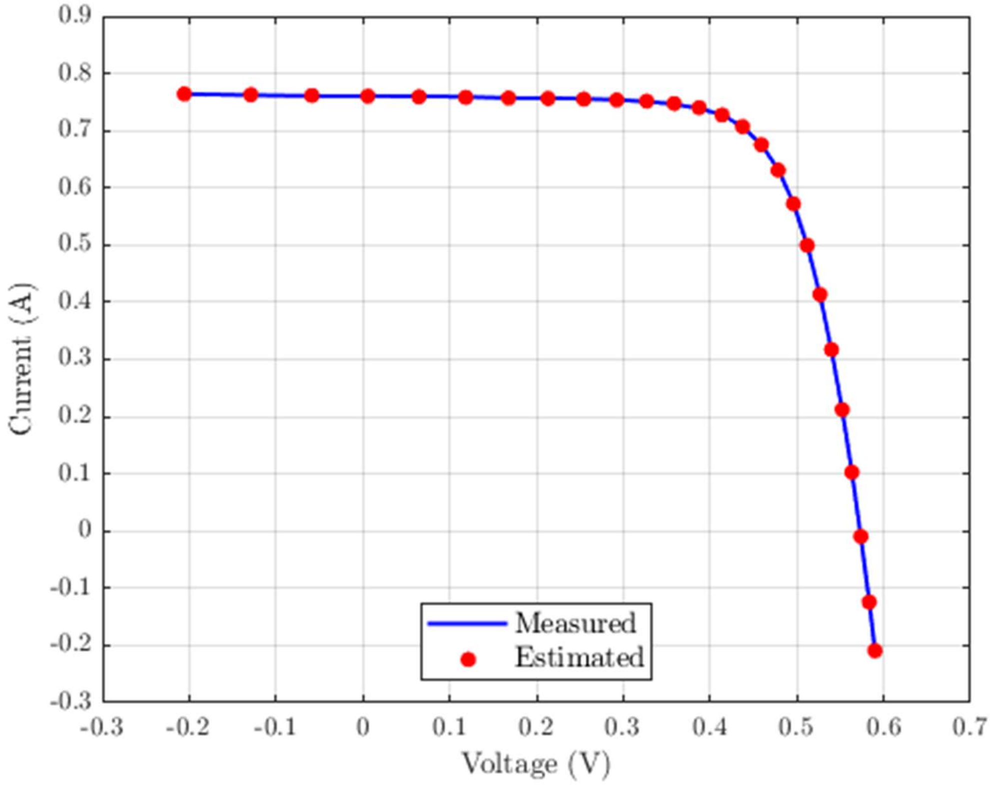


Figure 5. The measured and estimated data: P-V curve.



5. CONCLUSIONS

A Swarm MVMO method was proposed to estimate the parameters of the SDM of a PV cell. Numerical results show the ability and accuracy of Swarm MVMO in estimating SDM PV parameters correctly. In addition, the parameters obtained in the estimation process were also close to the values referenced in the literature. During the 30 simulations (runs), there was a large variation in RMSE values due to the characteristics of this algorithm, which generates, with each new simulation, a random population established within the maximum and minimum limits of each parameter.

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